

State of available capacity estimation for lead-acid batteries in electric vehicles using neural network

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Abstract

This paper reviews recent definitions of the state of charge (SOC) that are often used to estimate the battery residual available capacity (BRAC) for lead-acid batteries in electric vehicles (EVs) and identifies their shortcomings. Then, the state of available capacity (SOAC), instead of the SOC, is defined to denote the BRAC in EVs, which refers to the percentage of the battery available capacity (BAC) of the discharge current profile for the EV battery at the fully charged state. Based on the experimentation of different discharge current profiles, including theoretical current profiles and practical current profiles under EV driving cycles, the discharged and regenerative capacity distribution is proposed to describe discharge current profiles for the SOAC estimation. Because of the complexity and nonlinearity of the relationship between the SOAC and the capacity distribution at different temperatures, a neural network (NN) is applied to this SOAC estimation. Comparisons between the estimated SOACs by the NN and the calculated SOACs from the experimental data are used for verification. The results confirm that the proposed approach can provide an accurate and effective estimation of the BRAC for lead-acid batteries in EVs.

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1. Introduction

In a world where environmental protection and energy conservation are growing concerns, the research and development of various technologies in electric vehicles (EVs) is being actively conducted [1,2]. However, the application technology of EV batteries, namely the battery residual available capacity (BRAC) indicator for lead-acid batteries in EVs, cannot keep pace with the development of other EV technologies. The key problem arises from the highly nonlinear characteristics of EV batteries, leading to difficulty in the BRAC estimation and, thus, the driving range estimation for EVs.

Conventionally, the BRAC estimation for the EV battery has been represented by estimation of the battery state of charge (SOC). The purpose of this substitution is to

avoid the difficulty in defining the BAC at the fully charged state for various discharge current profiles of the EV battery. There are many papers describing various attempts to estimate the SOC for EVs using different approaches as summarized in Ref. [3]. Nevertheless, the SOC, in fact, is different from the BRAC for the EV battery. Theoretically, the SOC defines the ratio of the remaining active material to the total original active material inside a battery. In this sense, the SOC indicates only the battery state rather than the BRAC on which the EV driving range is dependent. Although the higher the SOC is, the more the BRAC can be exhibited at the same discharge current, they have no explicit quantitative relationship. For example, increasing the battery temperature or lowering the discharge current will cause an increase of the BAC at the same SOC. Fig. 1 shows the effect of discharge current and temperature on the BAC at the fully charged state of one lead-acid battery, where the SOC of the battery at the fully charged state is generally defined as unity.

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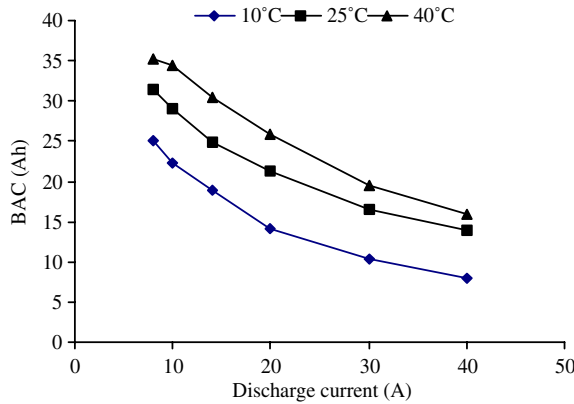


Fig. 1. Effect of discharge current and temperature on the BAC.

On the other hand, some direct estimation methods of BRAC for the EV battery have been explored by using coulometric measurement. The idea simply originated from the following basic equation:

$$C_r = C_a - q(t) \quad (1)$$

where C_r denotes the BRAC; C_a is the BAC measured from the discharge test as described in Section 3 and $q(t)$ is the discharged capacity given by

$$q(t) = \int_0^t I_d(t) dt \quad (2)$$

where $I_d(t)$ is the instantaneous discharge current. Since the BAC for the EV battery generally alters considerably, it has to be assumed as an appropriate value before the BRAC estimation is performed. So far, two methods have been adopted to approximate the value of the BAC at the fully charged state for the EV battery, either based on average discharge current [4,5] or based on a reference discharge current [6,7].

For the case of average discharge current, the SOC $p_{ave}(t)$ is defined as

$$p_{ave}(t) = 1 - q(t)/C_{ave}(t) \quad (3)$$

where $C_{ave}(t)$ is the average BAC corresponding to the average discharge current. The BRAC is estimated by using Eq. (3) without causing an error unless the discharge current varies significantly. This situation seldom occurs in the discharge current profiles of the EV battery. Fig. 2 shows four typical examples of the discharge current profiles for lead-acid batteries in EVs corresponding to the US federal urban driving schedule (FUDS), the US federal highway driving schedule (FHDS), the standard European reference cycle (ECE) and the Japanese mode 10.15

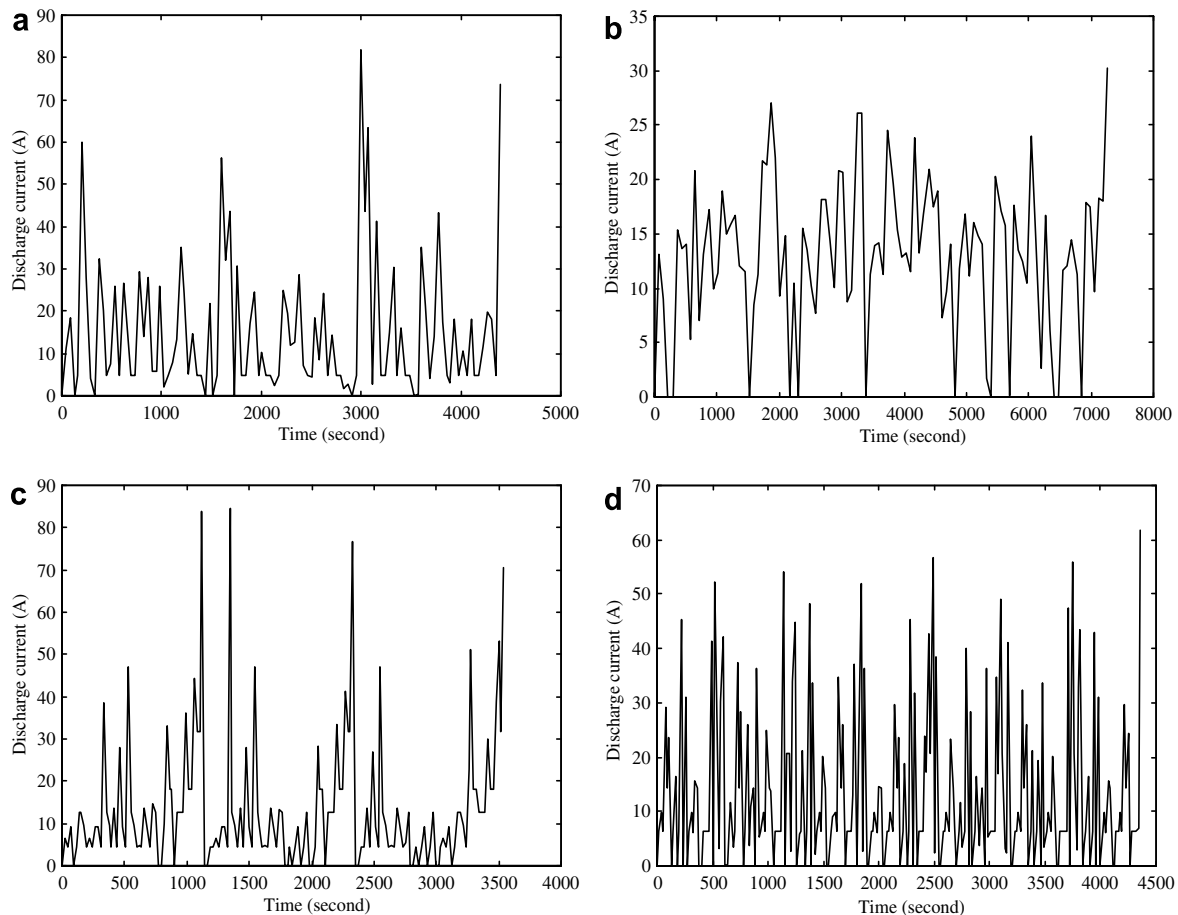


Fig. 2. Discharge current profiles of EV standard driving cycles without regenerative current: (a) FUDS; (b) FHDS; (c) ECE; (d) JM10.15.

(JM10.15). It indicates that the discharge current in these discharge current profiles varies significantly. Moreover, these kinds of variations lead to different BACs at the same temperature of 25 °C as shown in Table 1, even though their average discharge currents (ADCs) are all approximately equal to 13 A (about the 3 h discharge rate for the rated capacity of $C_N = 40$ A h).

For the case of a reference discharge current, the SOC $p_{\text{ref}}(t)$ is defined by:

$$p_{\text{ref}}(t) = 1 - \alpha(I_d)q(t)/C_{\text{ref}} \quad (4)$$

where C_{ref} is the reference BAC corresponding to the reference discharge current I_{ref} , such as the BAC at the 3 or 5 h discharge rate and $\alpha(I_d)$ is the corrective coefficient that is used to calculate the equivalent discharged capacity if the discharge current is either higher or lower than the reference discharge current. Obviously, the essence of this method is to determine the corrective coefficient. Previously, it was derived from the testing data of the constant current discharge. Lately, it is derived from the testing data of the pulse current discharge. Whichever test is used, the battery has to be tested by one discharge current either individually [6] or in combination with the reference discharge current [7] during the whole discharge period. These purposely designed tests provide the possibility of calculating the ratio of the BAC for the reference discharge current to that for the discharge current under testing, namely the corrective coefficient. However, the effect of discharge current profiles on the BAC is ignored, leading to creation of a significant error. Table 2 confirms this error even when the battery is under two-step discharge current profiles with simply swapping the sequence of discharge currents. Also, another drawback of this method is that the temperature cannot be formulated in the calculation of the corrective coefficient because of the nonlinear relationship between the BAC and the temperature under different discharge currents as shown in Fig. 3.

The purpose of this paper is to propose a new approach for BRAC estimation for the lead-acid batteries in EVs. The key is to define the state of available capacity (SOAC) $p_a(t)$ for discharge current profiles of the EV battery, instead of the SOC. Mathematically, it is written as

Table 1
BAC under different EV discharge current profiles

Profile	ADC (A)	BAC (A h)
FUDS	13.08	15.96
FHDS	13.11	25.05
ECE	13.21	13.05
JM10.15	13.12	15.43

Table 2
BAC under two step discharge current profiles

Discharge current profile	BAC (A h)
8 A for first 3 h and 20 A for other 0.38 h	31.66
20 A for first 0.38 h and 8 A for other 3.17 h	33.00
8 A for first 3.17 h and 20 A for other 0.1 h	27.33

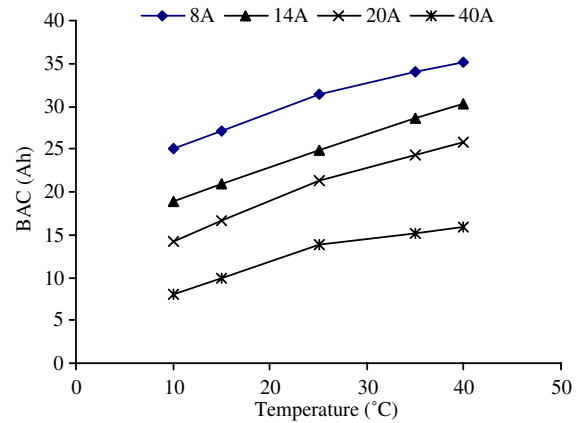


Fig. 3. Relationship between BAC and temperature for different discharge currents.

$$p_a(t) = 1 - q(t)/C_a \quad (5)$$

According to this definition, the SOACs of various EV discharge current profiles for lead-acid batteries are experimentally investigated under different temperatures. Based on the experimental data available, the SOAC estimation approach is proposed. Because of the complexity and non-linearity of the relationship between the SOAC and the capacity distribution at different temperatures, a neural network (NN) is applied to this SOAC estimation.

2. NN applications

Application of the NN to BRAC estimation for the EV battery provides a useful tool to solve the problems that exist in conventional methods. The key feature of the NN is its learning capability. When the NN is used for BRAC estimation of the EV battery, one needs only to consider selecting the parameters as inputs of the NN while the relationship between the output (the BRAC) and the inputs (related parameters) can be formulated by the training data. Therefore, the problem of the application of the NN to the BRAC estimation reduces to two fundamental issues. Namely, the appropriate training data should be obtained from experimental data as related to the EV battery, and the structure of the NN should accommodate the size and complexity of the relationship between the BRAC and its related parameters for the EV battery. Both problems will be addressed in designing the discharge current profiles and determining the inputs of the NN as well as processing the experimental data.

Recently, application of the NN either to the BAC estimation that can be used for the BRAC estimation through Eq. (1) or to the BRAC estimation for the EV battery has been investigated. For the former, a NN with three layers has been proposed [8,9], including the input, hidden and output layers. One neuron in the input layer represents the discharge current, while another neuron in the output layer represents the BAC at the fully charged state. To take the temperature effect on BAC into account, one more neuron to represent the temperature is added to the input

layer. With this NN, the BAC can be estimated at different discharge currents and temperatures. The accuracy of this NN is found to be better than that of the Peukert equation, which is often used in BAC estimation for lead-acid batteries in EVs. For the latter, two NNs with three layers, namely the input, hidden and output layers, have been proposed. The previous NN in Ref. [10] has four neurons in the input layer to represent battery terminal voltage, discharge current, temperature and internal impedance, and 10 neurons in the output layer to indicate the BRAC by using the SOC of 0–100% in steps of 10%. One discharge current profile, which simulates the typical operating condition of the EV battery, is used to test the battery. The experimental data, only covering one discharge current profile, are then used to train and verify the NN. The accuracy of this NN is only 10%. Similarly, the other NN lately proposed in Ref. [11] also has four neurons in the input layer to represent battery terminal voltage, discharge current, temperature and discharged capacity and one neuron in the output layer to indicate the BRAC by using the SOC between 0 and 1 in continuity. The experimental data are obtained both from the actual operation of EVs and laboratory testing, which represent various discharge current profiles of the EV battery. The part of the experimental data that reflect the features of the EV battery are used to train the NN, while the whole experimental data are used to verify the NN. The accuracy of this NN, as small as 5%, is much better than that of the previous one. However, the above mentioned two NNs have not yet taken into account the discharge current profile that has a strong influence on BRAC estimation.

In this paper, the discharged and regenerative capacity distribution is proposed to describe the discharge current profile of lead-acid batteries in EVs. Consequently, the capacity distribution and the temperature are selected as the inputs of the NN, while the output is the SOAC to represent the BRAC. The experimental data as related to the EV battery are processed to train and verify the proposed NN. The trained NN can then be ready for SOAC estimation.

3. Experiment

The NN for the SOAC estimation requires a lot of experimental data as related to the operating condition of the EV battery. To obtain these experimental data, the battery evaluation and testing system is built. As shown in Fig. 4, it consists of four main parts, namely a programmable charger, a programmable electronic load, a temperature controlled chamber and a data acquisition subsystem. The detailed description of this system can be found in Ref. [9]. With this system, the battery can be tested under different charge currents and discharge currents together with a pause at predefined temperatures. The lead-acid battery with the nominal voltage of 12 V is used for testing.

Since the BAC for different discharge current profiles dictates the driving range, various discharge current pro-

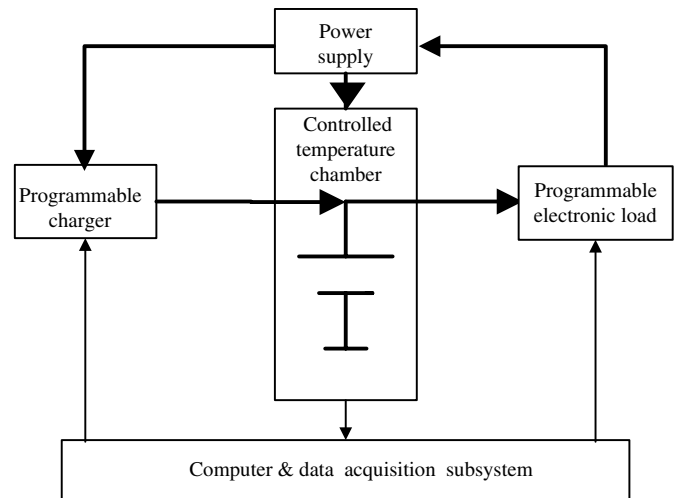


Fig. 4. Battery evaluation and testing system.

files that emulate various EV operating conditions are designed for the BAC test for the lead-acid batteries under investigation:

- Constant current discharges, where different discharge currents between $C_N/5$ and $C_N/1$ are used.
- Variable current discharges, where each discharge current profile has an average value approximately equal to $C_N/3$, are adopted. They can be categorized into two groups. One group is the random current discharge, including uniform distribution discharge current with the range of $C_N/10$ to $C_N/2$ and the normal distribution discharge current with the standard deviation of $C_N/8$. Another group is the standard EV driving cycle based current discharge, including the FUDS, FHDS, ECE and JM10.15. The discharge current profiles without regenerative current are shown in Figs. 2 and 5, while the discharge current profiles with regenerative current are shown in Fig. 6.

The BAC is defined as the quantity of electricity that can be delivered by the fully charged battery at a certain discharge current profile and temperature until the specified cutoff voltage is reached. Mathematically, it can be written as

$$C_a = f(V(t), I_d(t), T(t))|_{V(t)=V_{\text{off}}} \quad (6)$$

where $V(t)$ is the battery terminal voltage, $T(t)$ is the temperature and V_{off} is the specified cutoff voltage. Under this definition, the experiments for different combinations of discharge current profiles are performed at various temperatures ranging from 10 °C to 40 °C, where the battery at the fully charged state ($p_a(t) = 1$) is discharged until the specified cutoff voltage of 10.8 V is reached ($p_a(t) = 0$). Totally, 29 tests are conducted on the battery evaluation and testing systems. The experimental data are automatically collected. From the discharged capacities for all the tests, the BACs are obtained, and the corresponding SOACs can then be calculated by using Eq. (5).

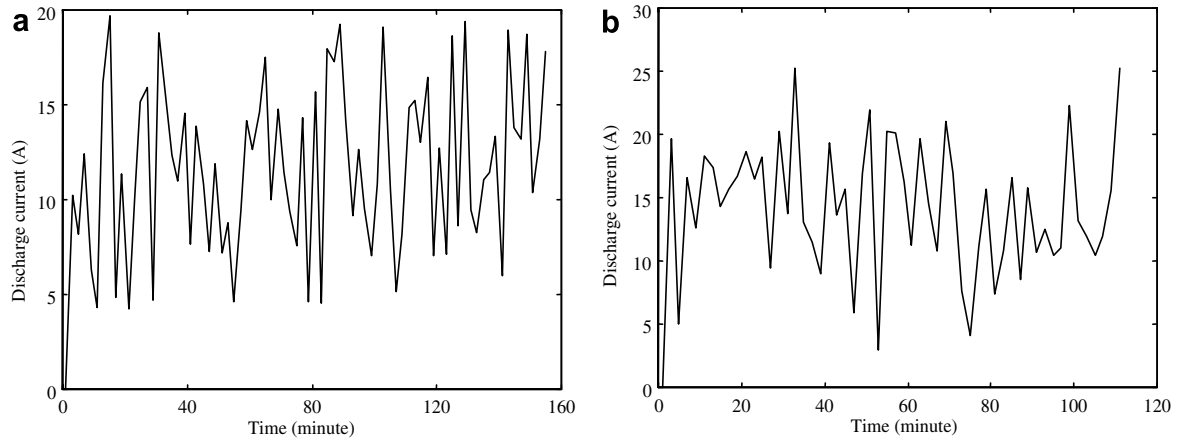


Fig. 5. Discharge current profiles of random current discharge: (a) UDDC; (b) NDDC.

4. NN modeling

The purpose of the NN model for the SOAC estimation is to describe the relationship between the SOAC and those easily measurable parameters, such as battery terminal voltage, discharge current, discharged capacity, regenerative capacity and temperature. Intuitively, the SOAC has a close relationship with the instantaneous value of battery terminal voltage and discharge current. Because of this rea-

son, they both are chosen as the inputs of the NN for BRAC estimation of the EV battery in Refs. [10,11]. However, this is not the case as conceived. Figs. 7 and 8 illustrate five examples of the relationships between the SOAC and the instantaneous values of battery terminal voltage at the temperature of 25 °C among a total of 29 tests, where the discharge current profiles are shown in Figs. 5(a), 2(a) and (c) and 6(a) and (c), respectively. They are corresponding to the UDCC, the FUDS and the ECE

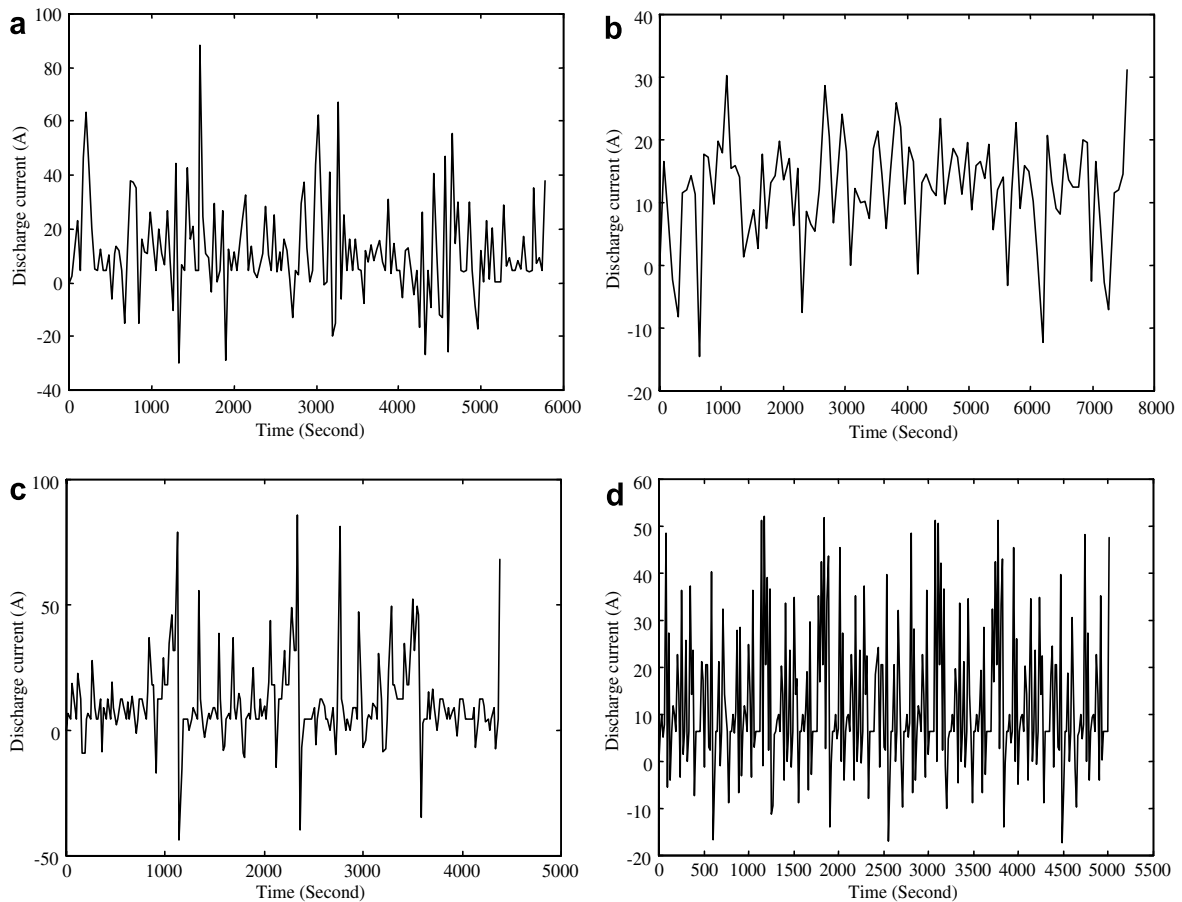


Fig. 6. Discharge current profiles of EV standard driving cycles with regenerative current: (a) FUDS; (b) FHDS; (c) ECE; (d) JM10.15.

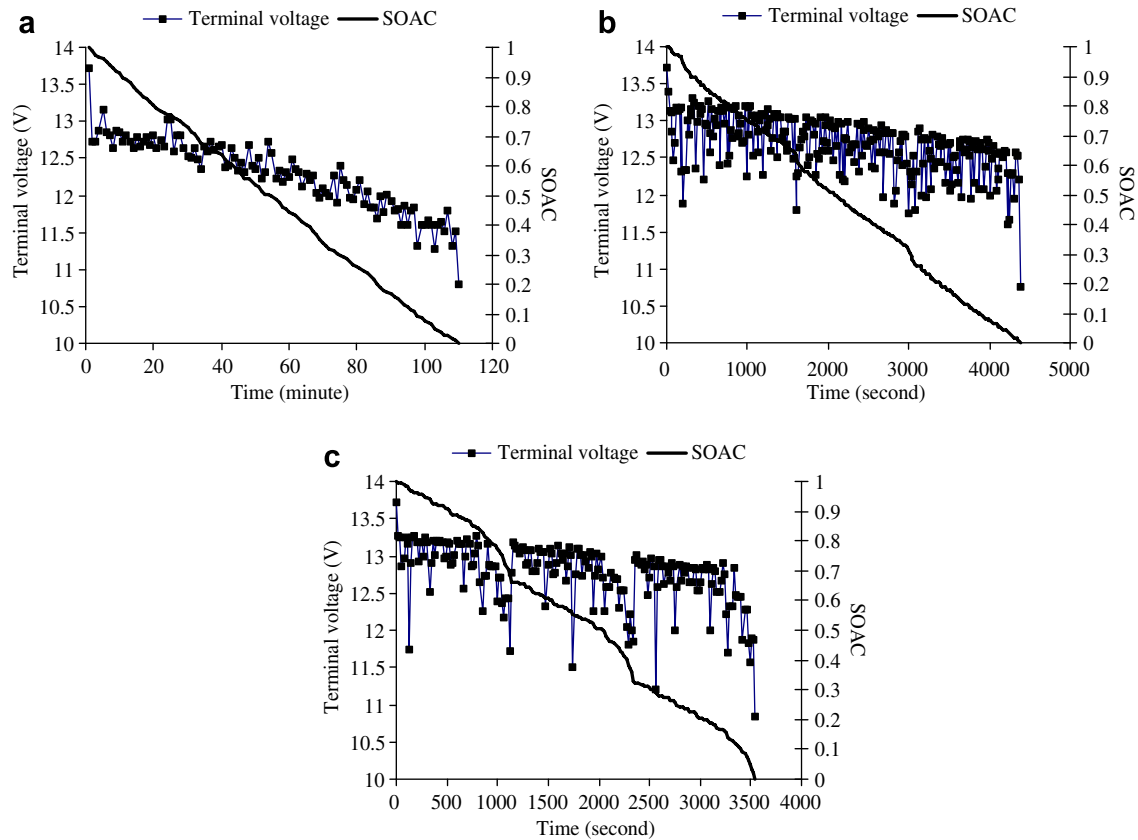


Fig. 7. Relationship between SOAC and battery terminal voltage for discharge current profiles without regenerative current: (a) UDDC; (b) FUDS; (c) ECE.

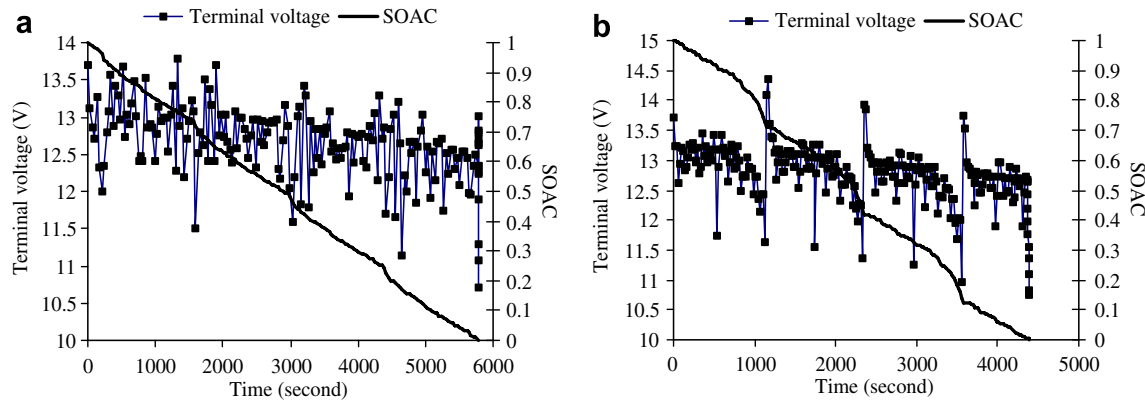


Fig. 8. Relationship between SOAC and battery terminal voltage for discharge current profiles with regenerative current: (a) FUDS; (b) ECE.

without regenerative current and the FUDS and the ECE with regenerative current. It can be observed that the battery terminal voltage changes considerably as a result of the significant variation of the discharge current, while the SOAC monotonously decreases with the progress of discharging. These phenomena demonstrate that the information embedded in the instantaneous value of the battery terminal voltage and the discharge current cannot offer direct contributions to the SOAC estimation. In contrast, the BAC for the EV battery is greatly influenced by the pattern of the discharge current (including the regenerative

current), namely the discharge current profile. So, the key of the SOAC estimation is to find an appropriate form to describe the discharge current profile as the inputs of the NN. Based on the experimental data under consideration, the discharged and regenerative capacity distribution is proposed to describe the discharge current profile for SOAC estimation.

As shown in Table 3, the discharged and regenerative capacity distribution based on the lower and upper current bounds of five current ranges, namely I_i^l and I_i^u ($i = 1, \dots, 5$), is adopted. As a result, the proposed NN for

Table 3
Lower and upper current bounds for capacity distribution

	<i>i</i>				
	1	2	3	4	5
I_i^l (A)	0	$C_N/5$	$C_N/3$	$C_N/2$	$C_N/1$
I_i^u (A)	$C_N/5$	$C_N/3$	$C_N/2$	$C_N/1$	100

SOAC estimation is shown in Fig. 9. This NN consists of three layers. The first layer, namely the input layer, has seven neurons:

- $X_1(t)$ —discharged capacity for $I_1^l \leq I_d(t) < I_1^u$;
- $X_2(t)$ —discharged capacity for $I_2^l \leq I_d(t) < I_2^u$;
- $X_3(t)$ —discharged capacity for $I_3^l \leq I_d(t) < I_3^u$;
- $X_4(t)$ —discharged capacity for $I_4^l \leq I_d(t) < I_4^u$;
- $X_5(t)$ —discharged capacity for $I_5^l \leq I_d(t) < I_5^u$;
- $X_6(t)$ —regenerative capacity for regenerative current;
- $X_7(t)$ —temperatures ($T(t)$) between 10 °C and 40 °C.

Considering the vector $X(t) = [X_1(t) \ X_2(t) \ X_3(t) \ X_4(t) \ X_5(t) \ X_6(t) \ X_7(t)]$, the proposed NN can then be described as a function that maps the input vector $X(t)$ to the output vector $p_a(t)$, namely, the SOAC at time t . The function form of SOAC estimation for this NN structure can be given as follows:

$$\hat{p}_a(t) = \sum_i^n W_i F(y_i) + b_1^o \quad (7)$$

where

$$F(y_i) = \frac{1 - \exp(-2y_i)}{1 + \exp(-2y_i)} \quad (8)$$

where $\hat{p}_a(t)$ is the single component of the vector that represents the value of the SOAC estimation; n is the number of neurons in the hidden layer; W_i ($i = 1, \dots, n$) are the weights between the hidden layer and the output layer, where only one neuron is adopted to denote SOAC; b_1^o is the bias at the output layer; and y_i ($i = 1, \dots, n$) is the input to the i th neuron in the hidden layer given by

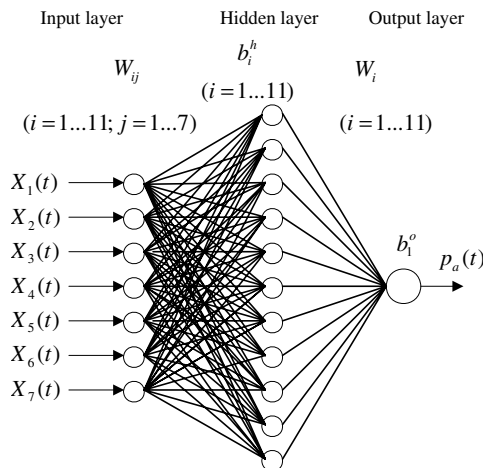


Fig. 9. NN for SOAC estimation.

$$y_i = \sum_{j=1}^7 W_{ij} X_j(t) + b_i^h \quad (9)$$

where W_{ij} ($i = 1, \dots, n, j = 1, \dots, 7$) are the weights between the input layer and the hidden layer and b_i^h ($i = 1, \dots, n$) are the biases at the hidden layer.

From the mathematical point of view, the NN shown in Fig. 9 has the relationship between its inputs and output that is approximated by n nonlinear terms, where n is the number of neurons in the hidden layer. Eight NN candidates are examined with the hidden neurons ranging from 8 to 15. Finally, a NN with 11 hidden neurons is selected to perform this study because there is no significant increase in the estimation accuracy for n greater than 11.

The learning algorithm of the NN is a numerical process that determines the connection strength, such as the weights among the layers, and the biases in each neuron. In the learning process, the validation data set is included for improvement of the generality of the NN. Under this condition, the learning process will be terminated when the error function on the validation data set begins to increase or the error function is smaller than the convergence tolerance, whichever is reached first. Here, the convergence tolerance is set at 10^{-5} . The error function E is defined as

$$E = \frac{1}{2} \sum_{k=1}^m (p_a(k) - \hat{p}_a(k))^2 \quad (10)$$

where m is the number of the training data, $p_a(k)$ is the SOAC calculated from the experimental data for the k th training data and $\hat{p}_a(k)$ is the corresponding value of the SOAC estimated from the NN.

The process of optimizing the parameters of this NN is performed by the Levenberg–Marquardt algorithm, one of the improved back propagation (BP) algorithms. This algorithm is a variation of Newton’s method designed for minimizing functions that are sums of squares of other nonlinear functions. So, it is well suited to minimizing the error function as defined in Eq. (10). In this algorithm, the square error E is expressed as a function of the parameters of the NN:

$$H = \{W_i, b_1^o, W_{ij}, b_j^h\} \quad (i = 1, \dots, n, j = 1, \dots, 7) \quad (11)$$

The optimum parameters of the NN can be obtained through the following iterative process:

$$H_{r+1} = H_r - A_r^{-1} g_r \quad (12)$$

where r is the iteration index, $A_r \equiv \nabla^2 E(H)|_{H=H_r}$ and $g_r \equiv \nabla E(H)|_{H=H_r}$ are the Hessian matrix and the gradient vector of E with response to the r th iteration, respectively. A detailed description of this algorithm can be found in Ref. [12].

5. Data preparation

The NN can make an estimation of the SOAC on the basis of the way it is learned from the training data. So,

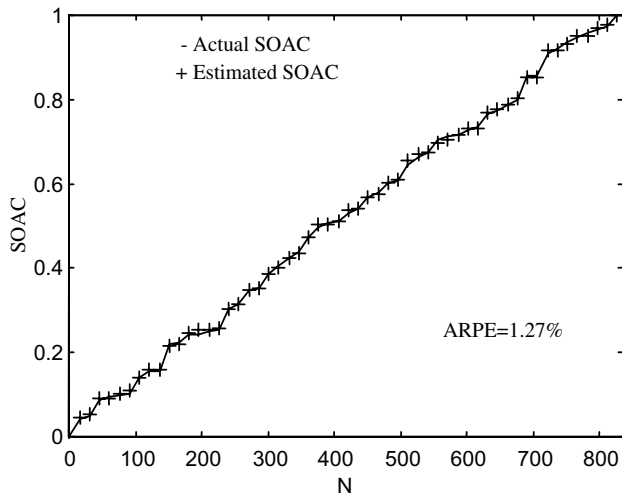


Fig. 10. Comparison between actual SOAC and estimated SOAC for training data set.

data preparation is very important for the NN to provide an accurate estimation of the SOAC. In the presence of different rates and durations under various discharge current profiles, the sampling rate for taking the experimental data should be unified. Since it is reasonable for the SOAC indicator in EVs to refresh its value in the order of seconds, one

second is selected as the sampling interval throughout the experimentation.

To train the NN by the BP algorithm effectively, the inputs of the NN are generally normalized by the following equation:

$$X_{jn}(t) = \frac{X_j(t) - X_{j\min}}{X_{j\max} - X_{j\min}} \quad (j = 1, \dots, 7) \quad (13)$$

where $X_{jn}(t)$ is the normalized value, $X_{j\max}$ and $X_{j\min}$ are the maximum and minimum values of the $X_j(t)$, respectively. After normalization, the data for each test are put together to form the whole data set with 2505 samples, which is then divided into the training, validation and testing data set.

6. Results and discussions

After the data preparation is finished, the training data set is used to train the NN, while the testing data set is used to verify the accuracy and effectiveness of the trained NN for SOAC estimation. To allow for comparison, the average relative percentage error (ARPE) is adopted. It is defined as:

$$\text{ARPE} = \frac{1}{N} \sum_{j=1}^N \frac{|p_{ae}(j) - p_{ac}(j)|}{|p_{ac}(j)|} 100\% \quad (14)$$

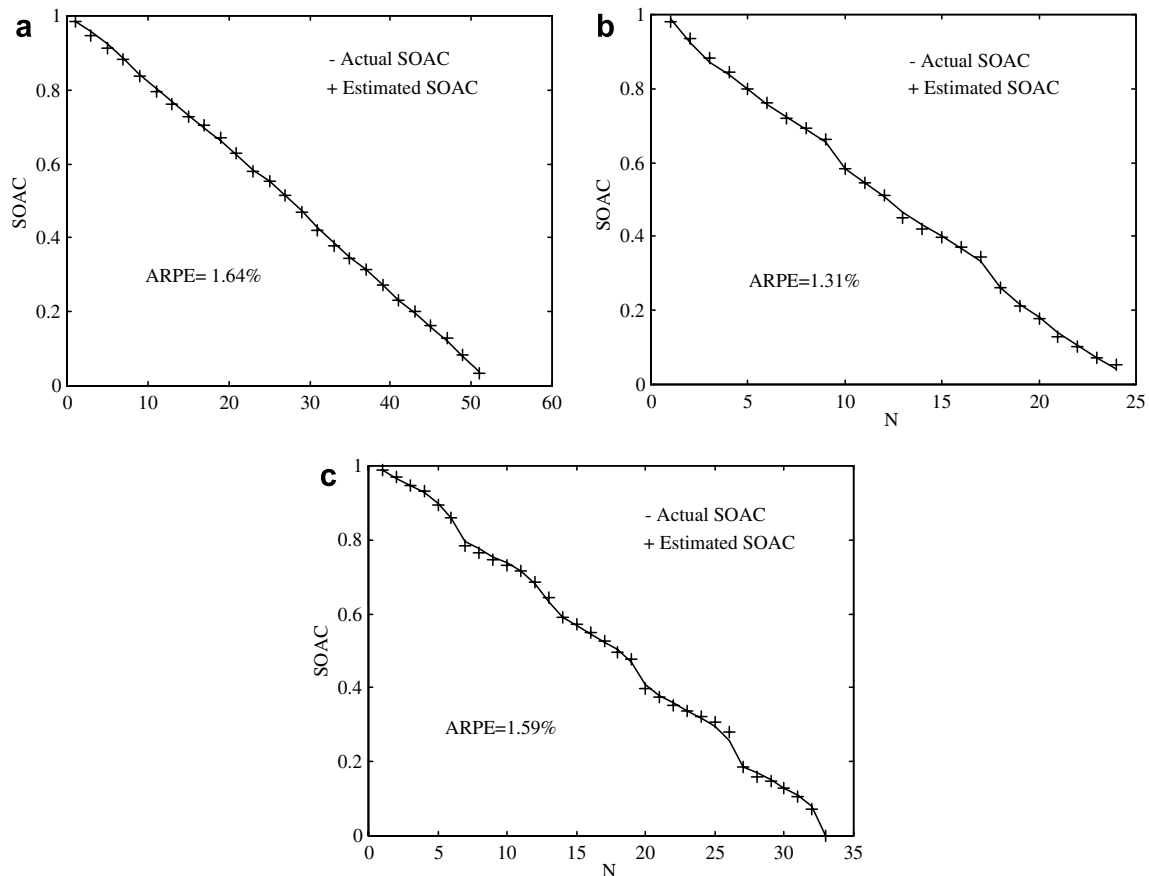


Fig. 11. Comparison between actual SOAC and estimated SOAC for discharge current profiles without regenerative current: (a) UDDC; (b) FUDS; (c) ECE.

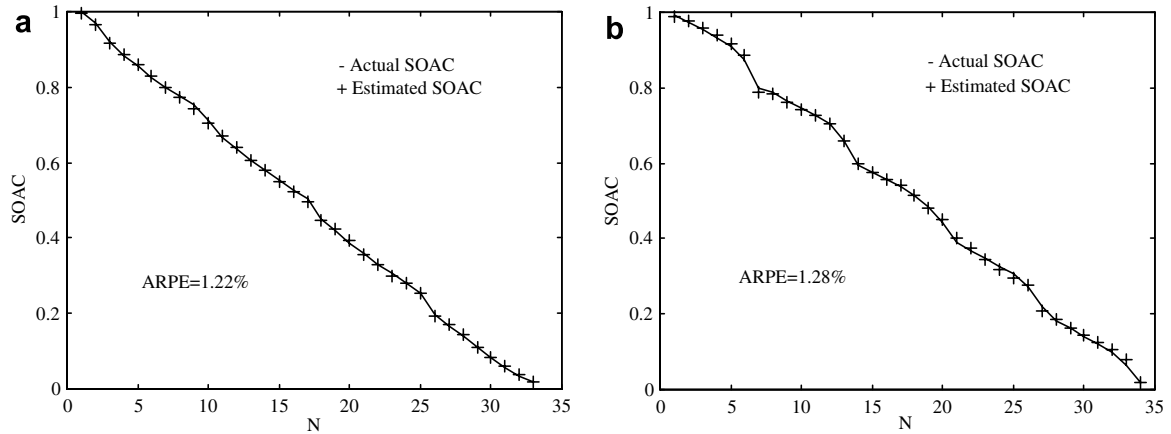


Fig. 12. Comparison between actual SOAC and estimated SOAC for discharge current profiles with regenerative current: (a) FUDS; (b) ECE.

where N is the number of training data or the data for each test in the testing data set, p_{ae} and p_{ac} refer to the estimated SOAC from the trained NN and the actual SOAC calculated from the experimental data, respectively. The ARPEs for both the training data set and the testing data set for each test are calculated. Fig. 10 shows the estimated SOAC and the actual SOAC for the training data set. It can be found that the SOAC estimation is of high accuracy, and the corresponding ARPE is only 1.27%.

To testify to the trained NN for SOAC estimation effectiveness, the testing data for each test are used to verify the trained NN. The results corresponding to the UDCC, the FUDS and ECE without regenerative current and the FUDS and ECE with regenerative current are, respectively, shown in Figs. 11 and 12. These figures illustrate that the proposed approach provides highly accurate estimation of SOAC for different discharge current profiles. It should be noted that the ARPEs of the proposed NN for SOAC estimation for all the testing data sets are within 2% as shown in Fig. 13. This demonstrates that the proposed

NN offers a significant improvement over the ARPEs of 10% [10] and 5% [11] in EVs where the NN is adopted.

The special features of the proposed NN to estimate BRAC in terms of SOAC are summarized as follows:

- The proposed NN exhibits a high capability of describing the complex and nonlinear relationship between BRAC and its related parameters of the EV battery. Actually, an analytical model can hardly describe such a relationship. Furthermore, the number of current ranges and the values of the lower and upper current bounds can be properly adjusted to adapt to the complexity and nonlinearity of the relationship between BRAC and its related parameters.
- The accuracy of the proposed NN for BRAC estimation under such a complex condition is even higher than that of the NNs in Refs. [10,11], while the corresponding discharge current profiles are even more complicated than the previous cases. This clearly indicates that the discharged and regenerative capacity distribution has a remarkable advantage over the instantaneous value of the battery terminal voltage and the discharge current used as the inputs of the NN for BRAC estimation.
- In the modeling process, the proposed capacity distribution and the structure of the NN for BRAC estimation are independent of the battery type. So, the proposed NN can readily be extended to other types of EV batteries provided that the experimental data of these batteries are available.

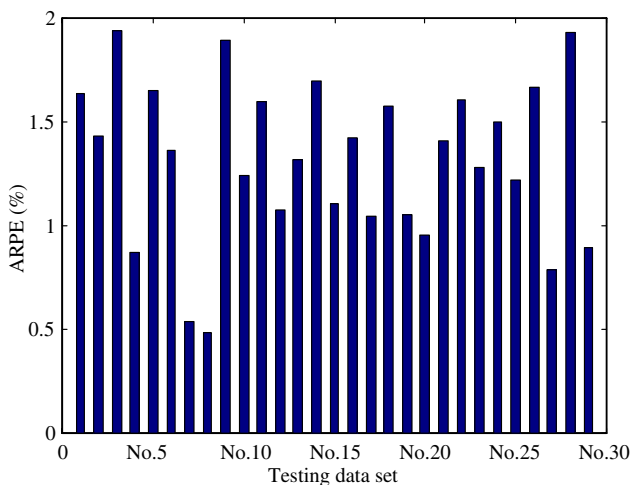


Fig. 13. ARPEs for all 29 testing data sets.

7. Conclusions

This paper has presented the application of the NN to BRAC estimation in terms of the SOAC for EVs. The effectiveness and accuracy of the SOAC estimation are verified by comparison of the estimated SOAC from the proposed NN with the calculated SOAC from the experimental data. It indicates that the proposed approach can estimate the SOAC within better than 2% regarding the experimental

data obtained from such a complex condition. Furthermore, the proposed approach can easily be extended to the SOAC estimation of other types of EV batteries.

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